

### Title:

Quantifying Post-Fire Ponderosa Pine Snags Using GIS Techniques on Scanned Aerial Photographs

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# **Principal Investigator:**

Dr. Erik Schiefer
Department of Geography, Planning, and Recreation
Northern Arizona University
Flagstaff, AZ

# **Student Investigator:**

Kevin Kent
Department of Geography, Planning, and Recreation
Northern Arizona University
Flagstaff, AZ



#### **Abstract:**

Snags are an important component of forest ecosystems because of their utility in forestnutrient cycling and provision of critical wildlife habitat, as well as associated fuel management concerns relating to coarse woody debris (CWD) loads. Knowledge of snag and CWD trajectories are needed for land managers to plan for long-term ecosystem change in the post fire regimes. This need will likely be exacerbated by increasingly warm and dry climatic conditions projected for the U.S. Southwest. One of the best prospects for studying fire-induced landscape change beyond the field-plot level, but still at a resolution sufficient to resolve individual snags, is to utilize the available aerial photograph record. Previous field-based studies of snag and CWD loads in the Southwest have relied on regional chronosequences to judge the recovery dynamic of Ponderosa Pine burns. This previous research has been spatially and temporally restricted because of ground survey extent limitations and uncertainty associated with the chronosequence approach (i.e. space-for-time substitution), which does not consider differences between specific site conditions and histories. This study develops highly automated methods for remotely quantifying and characterizing the spatial and temporal distribution of large snags associated with severe forest fires from very high resolution (VHR) landscape imagery. These algorithms utilize the sharp edges, shape, shadow, and contrast characteristics of snags and to enable feature recognition. Additionally, using snag shadow, the imagery time data, and location information, heights are estimated for each individual snag feature. Furthermore, a novel solution was developed for extracting individual snag features from areas of high snag density. Field survey data coincident to imagery coverage for post-fire Ponderosa Pine forests allowed calibration and accuracy assessment of these new tools. These new methods allow for broader estimation of snag dynamics in post fire landscapes while significantly lowering the human and material costs of conducting such surveys.



# **Background and Purpose:**

### Introduction and Purpose

Snags (dead standing trees) are an important part of forest ecosystems, yet data on volume, number, and density are hard to come by (Ganey and Vojta 2012). Even in areas where they have been studied, they exhibit large spatial and temporal variability (Morrison and Raphael 1993). Previously, studies of snags have relied on resource and time intensive ground surveys that have been necessarily limited in spatial extent (Passovoy and Fulé 2006). This research tests remote methods for measuring number and height of snags in post wildland fire Ponderosa Pine forests. Remote methods are unlikely to be as accurate as ground surveys, but the tradeoffs could make them highly appealing in many situations. These methods use existing resources, are much cheaper and time consuming than ground surveys, and can be scaled up to provide greater measurement at the landscape level.

Remote sensing provides significant opportunity for a better way to measure snags in a post-fire forest system. LIDAR is one obvious method for achieving this (Martinuzzi et al. 2009), but is still expensive to obtain and complicated to use (Laes et al. 2006). The existing aerial photography record provides a unique approach because it is relatively affordable, already has widespread coverage in many areas, and requires less technical sophistication. Furthermore, it is likely the only approach available for providing historical measurements.

In this research, an innovative new approach for estimating snag number and heights was developed using aerial photos as the source data. Digital scans of existing large-scale analog aerial photos are used to provide imagery of the study area and a feature extraction learning algorithm is applied to delineate snag areas based on their shadows. A novel process was developed for identifying the number and location of snag features in high-density areas where the algorithm delineated shapes were large and complex. The time, date, and locations of the aerial photos are then used to perform a trigonometric calculation estimating the height of each snag based on the length of its shadow. Finally, the results are compared to the ground data to provide an adjustment factor to better estimate the height of detected snags. This research is



conducted using plots from northern Arizona's 2000 Pumpkin Fire, with study areas coincident to plots previously ground-surveyed in 2001 and 2003 (Chambers and Mast 2005), with this data used for calibration and ground validation. Furthermore, this method is tested against a manual digitization of snags and a generic edge detection model to assess the relative accuracy of each.

### Background

In recent decades in the southwestern United States, fires have become larger and more severe (Haslem et al. 2011). Recent studies have suggested that contemporary burning is altering some regional ecosystems enough that Ponderosa Pine forests are failing to regenerate even decades after severe crown fires (Savage and Mast 2005, Roccaforte et al. 2012). Scientific- and management-related concerns associated with this ecologic change range from the loss of important forest carbon sinks (Dore et al.2008), to maintaining critical wildlife habitat (Chambers and Mast 2005), to concerns over reburning of areas due to heavy loads of standing and fallen snags (Passovoy and Fulé 2006). Roccaforte et al. (2012) emphasized that knowledge of snag trajectories are needed for land managers to plan for long-term ecosystem changes in the post fire regimes. Furthermore, this need will be exacerbated by an increasingly warm and dry climate, which is associated with the increasing number of severe forest fires (Seager and Vecchi 2010).



# **Study Location and Materials**

Research is conducted in the Ponderosa Pine forests of northern Arizona. The areas studied are located in Pumpkin fire burn area on the Kaibab and Coconino National Forests north of Kendrick Peak. Two plots that were surveyed by Chambers and Mast (2005) are extensively relied on for testing the research and assessing accuracy. The area is between 2300 and 2550 meters in elevation on generally flat surfaces ( <10% slope) and the plots consist of 50 x 200 m rectangles.

The source materials consist of digital scans of existing true color 1:12000 United States Department of Agriculture (USDA) aerial photos scanned at 12 microns to give a resolution of approximately .18 meters/pixel. Of the three Pumpkin fire plots studied by Chambers and Mast, only two are covered by the high resolution imagery taken after the Pumpkin fire. Each plot is shown on two separate photos, resulting in 4 available scenes for study. To perform the feature extraction, a model was created using Textron System's Feature Analyst software for ESRI's ArcGIS. The remainder of the Analysis is done using ArcGIS Desktop Advanced 10.1, including the Spatial Analyst extension and the Python 2.7 integrated development environment.

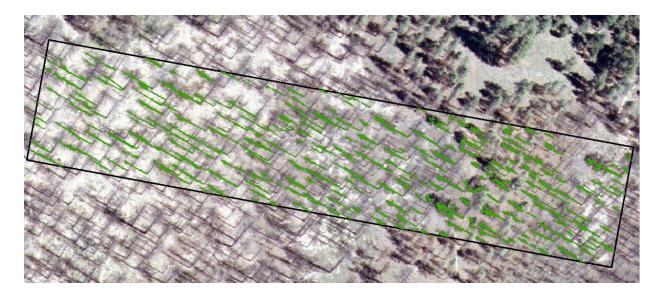


### **Study Methods and Process:**

### Feature Analyst Method

After obtaining imagery from the USDA, the scenes were georeferenced from control points obtained in the field using hand held GPS. Plots were constructed using GPS and bearing data from Chambers and Mast (2005). Using the feature extraction tool Feature Analyst, a learning algorithm was developed to automatically resolve snag features from the plots. After testing hundreds of different parameter configurations, a simple double pass learning method was deemed the most effective, consisting of creating a training sample of snag features and using a simple feature extraction run twice over the scene while employing a minimum shape size and applying a smoothing filter. This configuration was saved as an exportable accelerated feature extraction (.afe) file that was subsequently used on the other scenes using the Feature Analyst software, creating a polygon shapefile showing snag features (Figure 1).

Figure 1. Feature Analyst polygons, scene A, plot 1.





### Edge Detection Method

To give perspective on the feature extraction method, a simpler method of using edge detection was employed on each of the four scenes. To do this, an image is rotated so the snag shadows are vertically oriented. A gradient edge detection function is performed using ArcGIS Image Analysis followed by a majority filter to reduce noise. A binary reclassification is done using visual evidence of natural breaks in the scene between snag and non-snag areas. The snag zones are expanded by 1 pixel in each direction, the scene is rotated back to its original orientation, and the snag raster zones are then converted to polygons that, like in the Feature Analyst method, represent the location and lengths of each snag's shadow.

#### Manual Digitization Method

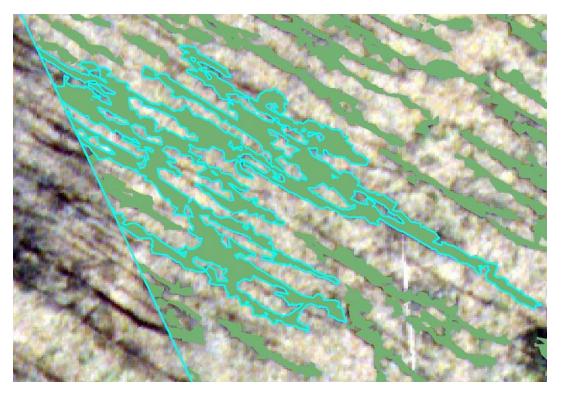
In this method, the shadows of snags were digitized in each of the four scenes by drawing polylines in ArcGIS in a new shapefile on top of the existing georeferenced imagery. They were digitized as lines representing the center of a snag shadow. This manual drawing automatically includes the lengths of each shadow in the shapefile geometry. A new tool was also constructed using ArcObjects for Visual Basic to assist in the rapid digitization of snags while assigning each snag to a decay class. However, due to time constraints, decay class was left outside the scope of the final analysis.



## Complex Polygons

In some cases, especially areas a high density of snags, large complex polygons where many parallel snag features are joined by short bridges of non-snag features are created (Figure 2).

Figure 2. Complex snag area polygon, scene D, plot 2.



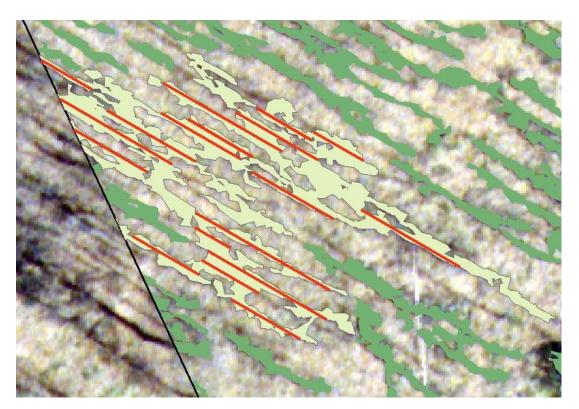
This poses a serious problem because there is not an easy way to automate the breaking of such complex polygons into separate features. With simple polygons, the longest midline can be converted to a polyline to estimate the length for each feature, but this is not possible with large, complex polygons. Fortunately, a novel solution was developed that is one of the most exciting outcomes of this research.



### Fishnet Snag Detection

To overcome this hurdle of complex snag polygon shapes, a fishnet is constructed. A fishnet is a dense grid of polylines, in this case a large number of columns but only one row, where the column spacing is half that of the average snag polygon width. The fishnet is rotated by the user to line up in parallel to the snag shadows, with this angle of rotation determining the sun's azimuth, and laid over the detected snag area polygons. A scripting tool packaged as an ArcGIS toolbox tool was developed to automate the delineation of snag features from all polygons, including the large complex ones, and to calculate the height of each snag. The script consists of an identity tool that attaches the polygon IDs to the fishnet lines and then goes polygon by polygon, finding the longest line in each polygon and outputting these as snag polylines. In complex polygons, where it is clear to the human eye that the polygon consists of multiple snag features, it flags all the local spatial maxima (in terms of length) of the parallel fishnet lines in a polygon (Figure 3).

Figure 3. Complex polygon with snag features detected from fishnet local maxima.





After selecting all the flagged local maxima lines, the script exports them to a new shapefile showing the position of all the snag shadows detected with noise removed (i.e. lines shorter than a user specified minimum length).

## Height Calculation

With lines representing the shadow of each snag detected, the script moves on to calculate the estimated height of each snag. This involves using the US Naval Observatory's Sun Altitude/Azimuth calculator website to determine the angle of the sun's elevation, based on the previously derived azimuth of the sun, the location of the scene, and the date on which the imagery was captured (US Naval Observatory 2015). The angle of the sun is used as an input in the script and a simple trigonometric function is employed to calculate the height of each snag in the attribute table.

$$H = Height \ of \ snag \qquad L = Length \ of \ snag's \ shadow$$

$$a = angle \ of \ sun's \ elevation \ (degrees)$$

$$H = L * TAN(a)$$

Following this, a final count and average snag height is available for the scene by viewing the attribute table summary statistics.

#### Adjustment

It was readily apparent that all methods were underestimating the height of the snags so much that many features (as many as 75% of possible snag lines in some scenes) were below the minimum height, disqualifying them from being counted. To alleviate this compounding problem, a height adjustment was performed on the outputs from the Feature Analyst and edge detection methods. Adjustment was not performed on the digitized snags because the number of snags detected using this method was largely accurate and there was no noise needing to be filtered out. Using data from Chambers and Mast (2005), the minimum height of the measured snags for each plot is found after removing outliers (height outliers are those shorter than 1.5 inter-quartile ranges less than the first quartile). In the initial estimated output, the average height



of all detected snags (n) larger than the minimum measured height is normalized to the average height of the largest n snags in the ground-survey data. This system is employed because it was presumed the larger snags were detected with the greatest accuracy. To better explain this system the following example from the Feature Analyst method is described. Plot 1 had a minimum (outlier removed – values less than 1.5 interquartile ranges below quartile 1) ground-surveyed height of 8.35m. The remotely sensed data from scene A/Plot 1 initially has 40 snags 8.35m or higher; the average height of which is 10.37m. The largest 40 snags (of 325 in total) in the ground-survey data have an average height of 17.57 meters. 17.57/10.37 =1.69. Thus, a height adjustment factor of 1.69 is used on the all the snag features in scene A, creating a new adjusted height for each snag in the attribute table, after which 176 snag features are above the minimum height threshold..



## **Accuracy Assessment:**

After the initial analysis was complete, results were compared to the ground survey data, shown in Table 1.

Table 1. Results from Feature Analyst (\_FX), Edge Detection (\_ED), and Digitization Methods (\_DIG).

| Plot                    |       | P1B   |        |       | P2B   |        |
|-------------------------|-------|-------|--------|-------|-------|--------|
| Scene                   | A_FX  | B_FX  | Ground | C_FX  | D_FX  | Ground |
| Snags                   | 176   | 117   | 328    | 125   | 147   | 283    |
| Adjusted Average Height | 12.32 | 13.44 | 13.30  | 14.06 | 13.17 | 12.70  |
| Adjustment Factor       | 1.69  | 1.53  | X      | 1.20  | 1.45  | Χ      |
| Pre-Adjustment Snags    | 40    | 51    | Χ      | 103   | 79    | Χ      |
| Pre-Adjustment Avg. Ht. | 10.37 | 11.32 | Χ      | 12.61 | 10.80 | Χ      |
|                         |       |       |        |       |       |        |
| Plot                    |       | P1B   |        |       | P2B   |        |
| Scene                   | A_ED  | B_ED  | Ground | C_ED  | D_ED  | Ground |
| Snags                   | 237   | 141   | 328    | 132   | 176   | 283    |
| Adjusted Average Height | 13.90 | 16.53 | 13.30  | 13.42 | 14.31 | 12.70  |
| Adjustment Factor       | 1.47  | 0.90  | Χ      | 1.43  | 0.75  | Χ      |
| Pre-Adjustment Snags    | 135   | 141   | Χ      | 76    | 192   | Χ      |
| Pre-Adjustment Avg. Ht. | 11.27 | 18.37 | Χ      | 11.05 | 18.30 | Χ      |
|                         | I     |       |        |       |       |        |
| Plot                    |       | P1B   |        |       | P2B   |        |
| Scene                   | A_DIG | B_DIG | Ground | C_DIG | D_DIG | Ground |
| Snags                   | 285   | 277   | 328    | 259   | 267   | 283    |
| Average Height          | 10.74 | 10.81 | 13.3   | 6.87  | 5.89  | 12.7   |



Accuracy for each scene and method as a percentage of the ground survey data is shown in Table 2.

Table 2. Accuracy of each method as a percentage of ground data (\*digitization results unadjusted).

| Plot P1B           |                |                |                |                |                 |                 |
|--------------------|----------------|----------------|----------------|----------------|-----------------|-----------------|
| Method             | A_FX           | B_FX           | A_ED           | B_ED           | A_DIG           | B_DIG           |
| Adjusted Count*    | 53.66%         | 35.67%         | 72.26%         | 42.99%         | 86.89%          | 84.45%          |
| Adjusted Height*   | 92.63%         | 101.05%        | 104.51%        | 124.29%        | 80.75%          | 81.28%          |
|                    | ļ              |                |                |                |                 |                 |
|                    |                |                |                |                |                 |                 |
| Plot P2B           |                |                |                |                |                 |                 |
| Plot P2B<br>Method | C_FX           | D_FX           | C_ED           | D_ED           | C_DIG           | D_DIG           |
| -                  | C_FX<br>44.17% | D_FX<br>51.94% | C_ED<br>46.64% | D_ED<br>62.19% | C_DIG<br>91.52% | D_DIG<br>94.35% |
| Method             | _              | _              | _              | _              | _               | _               |

The average accuracy of each method is shown in Table 3.

Table 3. Average accuracy by method (\*digitization results unadjusted).

| Method           | FX      | ED      | DIG    |
|------------------|---------|---------|--------|
| Adjusted Count*  | 46.36%  | 56.02%  | 89.30% |
| Adjusted Height* | 102.02% | 111.79% | 65.63% |

One more assessment was devised to test the accuracy of the heights derived from Feature Analyst method on a 1-to-1 snag basis. Using data from Chambers and Mast's (2005) ground survey a point shapefile was created showing the location of each snag. Because of error introduced from impreciseness in their snag location information, plot coordinates, imagery georeferencing, and general inaccuracy of the snag detection methods, it was impossible to compare output snags to their ground counterparts on a 1-to-1 basis across entire scenes. However, some snags are so isolated and distinct that they could be visually identified as the same features as their ground counterparts with a high degree of certainty. Ten of these pairs



were identified in each Feature Analyst scene and the average height as compared to ground data is shown in Table 4.

Table 4. 1-to-1 accuracy assessment from a sample of Feature Analyst derived height data, as a percentage of ground data.

| Plot                       | P'      | IB      | P2B     |         |
|----------------------------|---------|---------|---------|---------|
| Scene                      | A_FX    | B_FX    | C_FX    | D_FX    |
| Adjusted Height Accuracy   | 111.15% | 118.77% | 122.12% | 115.96% |
| Unadjusted Height Accuracy | 65.77%  | 77.63%  | 101.77% | 79.97%  |

As shown in Table 3, manual digitization provides a high degree of accuracy (84-95%) for estimating the total number of snags in a scene, but only moderately accurate and highly variable height estimation (46-81%). Both the Feature Analyst and edge detection method severely underestimate the number of snags in a scene but on average are accurate at estimating height when using an adjustment.



### **Key Findings:**

1. Remote methods for inventorying post-fire snags can provide a way of estimating snag numbers and height in post-fire environments.

The results among the different methods tested varied in accuracy but provide a strong starting point for investigating the use of aerial photos for creating estimates of number and height of snags in an area. These methods clearly need refinement and further, broader testing, but they have shown to provide promising results for use in the area in which they were developed. At the very least, this research is ready to provide snag number and height estimations that are within the correct order of magnitude, which, although still rough could be useful.

2. Large-scale imagery (1:12000 or greater) is necessary for resolving snag features.

It was originally intended that this research would have a broader scope by using data from more plots on different fires, but the lack of suitable imagery precluded this. 12 micron scans of 1:20000 color air photos were investigated, but deemed too coarse to be able to resolve individual snag features without resulting in a very low degree of accuracy. This is applicable to natively digital aerial photos that have pixel resolutions of .2 meters or higher.

3. Complex polygons encompassing many snags can be systematically manipulated to resolve individual snag features.

Using the novel fishnet method and local maxima script, a serious impediment was overcome in delineating snag features from high-density areas. By finding all the local maxima, instead of fixed number of the longest lines, there is no theoretical limit to how complex a polygon could be and still resolve snags. While this was an important breakthrough, it is imperfect and more development is needed to resolve issues for vertical alignment of snag shadows.



### **Management Implications and Related Work:**

1. Remote sensing can provide land managers with new tools for estimating post-fire snag data.

Clearly, remote methods for measuring forest dynamics is an important field for land managers to take interest in. With improvements in accuracy and broad scale testing of these methods, they can provide a cheap new tool for land managers and researchers to quickly and efficiently measure fire impacts. In an era of budgetary concerns and limits on human resources remote sensing has the potential to significantly decrease data collection costs. Furthermore, remote sensing, and especially automated techniques, provides an important opportunity for greatly expanding the scale on which detailed forest data can be obtained, from the plot level to the landscape level. As discussed earlier, LIDAR is another possible avenue for collecting such data (Martinuzzi et al. 2009), but traditional air photos are much more ubiquitous, cheaper to obtain, and require less expert knowledge to analyze.



#### **Future Work:**

While this research represents a significant first step for using remote methods to inventory snags in post-fire settings, more work is needed to refine the accuracy and gain a greater understanding of the limitations of remote surveys.

The methods described here need to be tested on a greater number of sites. These should encompass sites of different forest type, maturity, density, burn severity, slope, and locations. Accuracy needs to be categorically tested by snag class to determine how accurate these methods are for different size snags. The process for calculating height from shadows needs to be compared with results from imagery taken at different times of the day and with a broader range of sun elevation angles.

The algorithm used by the Feature Analyst method was a good start, but limited by the source imagery. In addition to true color imagery, color-infrared images could greatly increase the accuracy in distinguishing snag features, especially when the ground cover is live vegetation.

The devised fishnet method for resolving individual snags from complex polygon features does a good job with horizontally bridged-together features, but is ineffective at separating snags whose shadows are vertically aligned inside one polygon. A new approach at resolving this issue would be needed, perhaps by setting a relative length threshold for keeping two features on one line when appropriate.



#### **Deliverables:**

### Conference Presentation:

Finished 2014 at International Association of Wildland Fire Conference

## Software:

Feature Analyst model completed and submitted Python Script and accompanying ArcGIS ArcToolbox Tool completed, documented, and submitted.

#### Publication:

In preparation, expected submission April 2015.

Expected Citation: Kent, K., Schiefer, E., Chambers, C., Mast, J. Quantifying Post-Fire Ponderosa Pine Snags Using GIS Techniques on Scanned Aerial Photographs. To be submitted to Applied Remote Sensing.

### Master's Thesis:

To be defended summer 2015.



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